Approaches to DA Intercomparison

by

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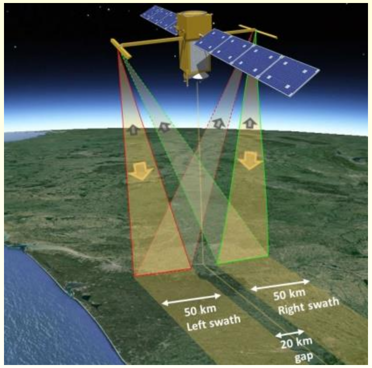
June 15, 2016 – Hydrology splinter session - 11:30

Outline

- Position of the inverse problems for river hydraulics in SWOT context
- Data Assimilation features in the ST hydraulic models
- Inversion capabilities: current results
- Conclusions

What is river hydraulic parameters inversibility with SWOT data?

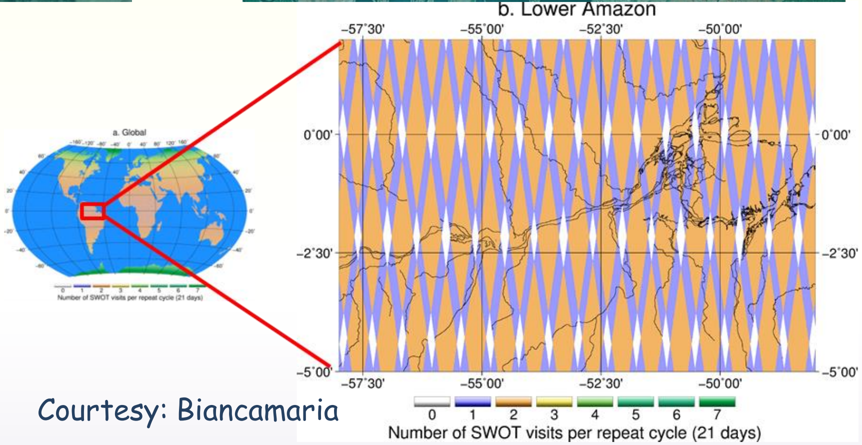


Garonne river (Toulouse, France)

Congo River (Border of Congo and RDC)

Challenging points:

- **Unobservable river bathymetry?**
- **Link between basal friction an topography?**

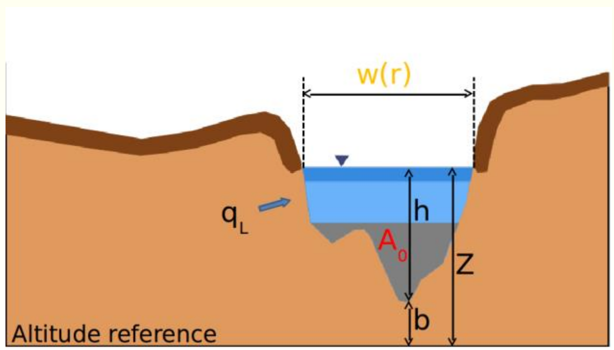


Courtesy: Biancamaria

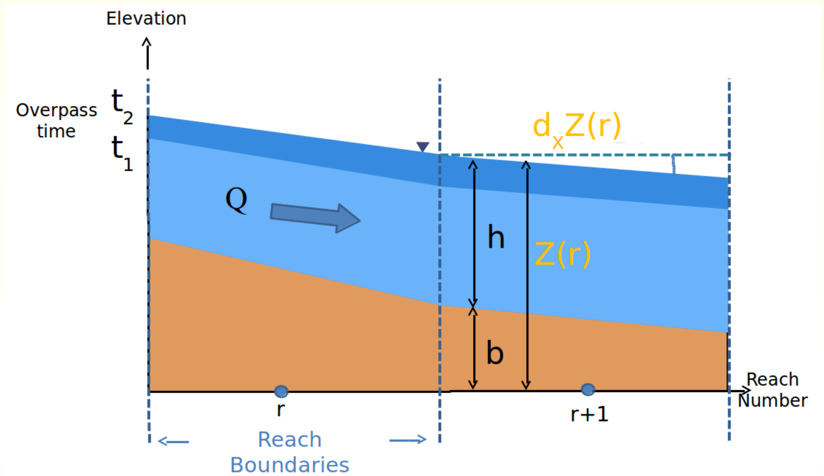
Tanana River (Alaska, US)

Position of river parameters inverse problems in a SWOT context

- Reach averaged SWOT obs. (Z, W, Slope) + temporal revisits
- No low flow bathymetry and friction observed

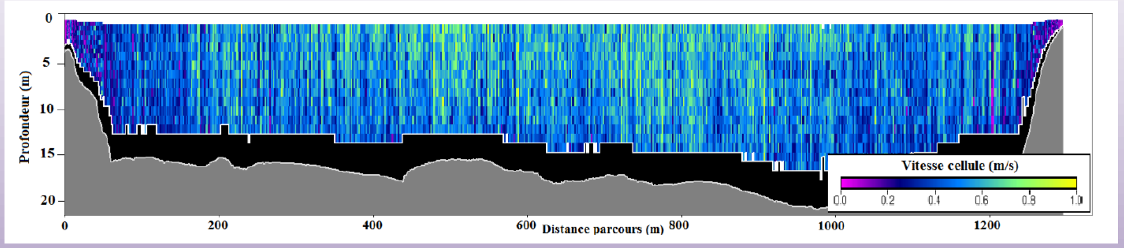


Case of single thread channels



→ Under-constrained inverse problems
→ Triplet (Q, A0, K) Equifinality (e.g., Aronica et al. 1998, Roux and Dartus 2008, Garambois and Monnier 2015)

A real velocity profile, Rio Negro at Novo Airão in 12/15 (ADCP Measurement) – Source Paris 2015



Principle of DA for parameter inference in hydraulic models

- The 1D Saint-Venant equations

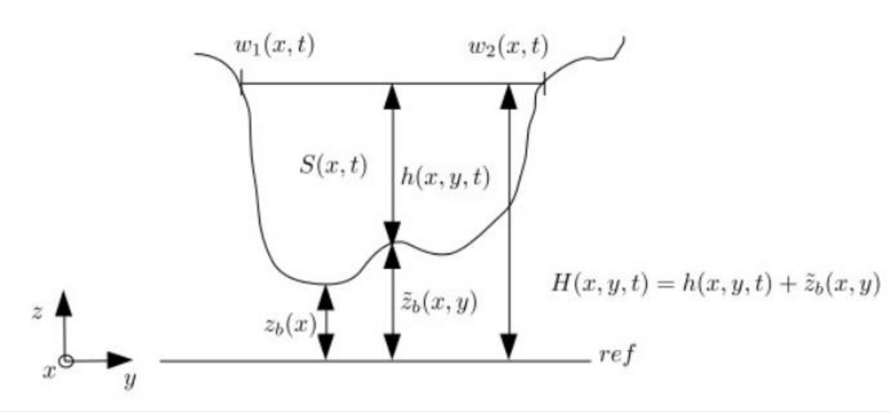
1D Shallow water :

$$\begin{cases} \dfrac{\partial S}{\partial t} + \dfrac{\partial Q}{\partial x} & = \quad 0 & (4.1) \\ \dfrac{\partial Q}{\partial t} + \dfrac{\partial}{\partial x}\left(\dfrac{Q^2}{S} + P\right) & = \quad g\displaystyle\int_0^h (h-z)\frac{\partial \tilde{w}}{\partial x}dz - gS\frac{\partial z_b}{\partial x} - gSS_f & (4.2) \end{cases}$$

$$H = z_b + h$$

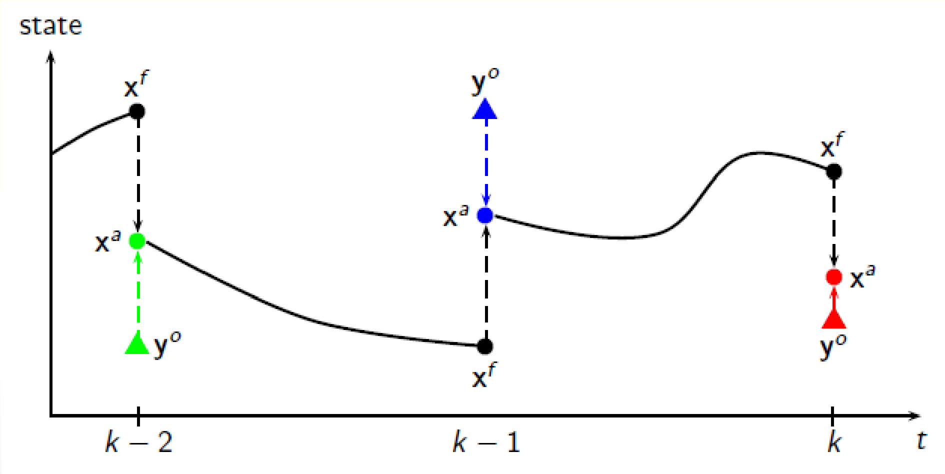
$$S_f = \frac{|Q|Q}{K^2 S^2 R_h^{4/3}}$$

Q : Discharge.
S : Wet-cross section.
H : Water elevation.
z_b : Bed elevation.
h : Water depth.
K : Manning-Strickler (roughness coefficient).
R_h: Hydraulic radius.

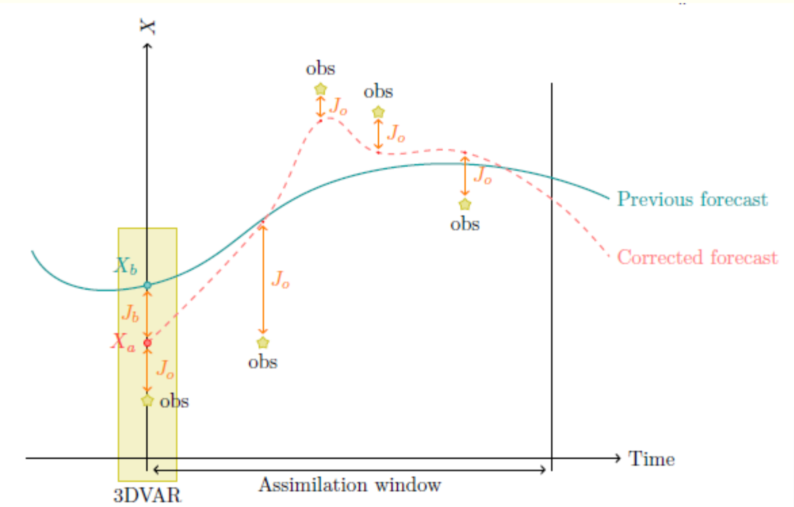


Principle of data assimilation (DA)

- Estimate x^a of the true input x^t given a backgroung x^b and partial observations with given covariance matrix. Stochastic methods (~Kalman filters)



- Minimization of a cost function J using optimization and adjoint method (Variational methods)



[Nodet 2012]

→ **Importance of observation operators**

→ **Physics of (Var) DA relies on the definition of cost functions J**

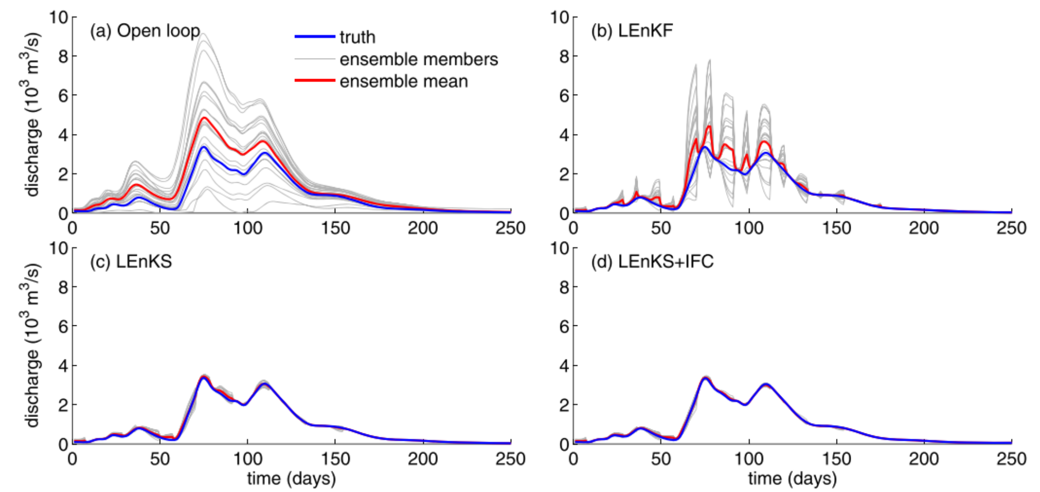
→ **∃ conditions of equivalence between 4D-Var and Kalman filter algorithms**

Data assimilation features in the ST hydraulic models

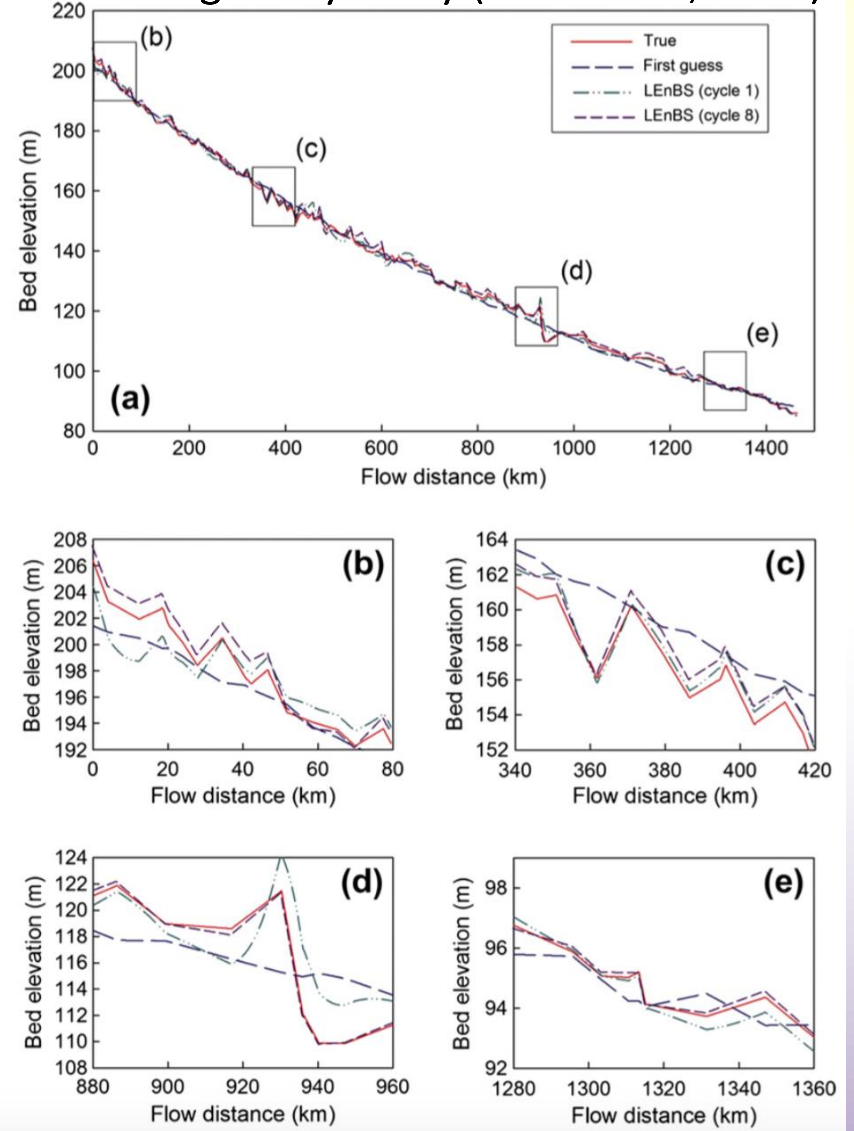
Model	Model paradigm	Assim. method	Identified variables	Usable Data	Data assimilation references
DassFlow	0,5D reach averaged 1D full Saint-Venant 2D SW (fully MPI)	4D-VAR	Q, K, A/zb,	In situ Q, h + W, S and Z	[Honnorat et al. 2006, 2008] [Hostache et al. 2009] JoH, [Lai and Monnier 2010] JoH, [Monnier et al.] in rev. [Brisset et al.] x2 in final redaction
LisFlood-FP	1,5D 1D full Saint-Venant FP - Diffusive wave	ENKf	Q	W, Z, S	[Biancamaria et al. 2011] RSE [Yoon et al. 2012] JoH [Andreadis & Schumann 2014] AdWR [Munier et al. 2015]
Mascaret	1,5D 1D full Saint-Venant FP storage	EnKf	Q	W	[Ricci et al. 2012] HESS [Habert et al. 2016] JoH
SIC^2	1,5D 1D full Saint-Venant FP storage	4D-VAR	Q, K, A/zb,	In situ Q, h + W, S and Z	[Gejadze and Malaterre 2016] IJNMF (accepted)

LISFLOOD-FP

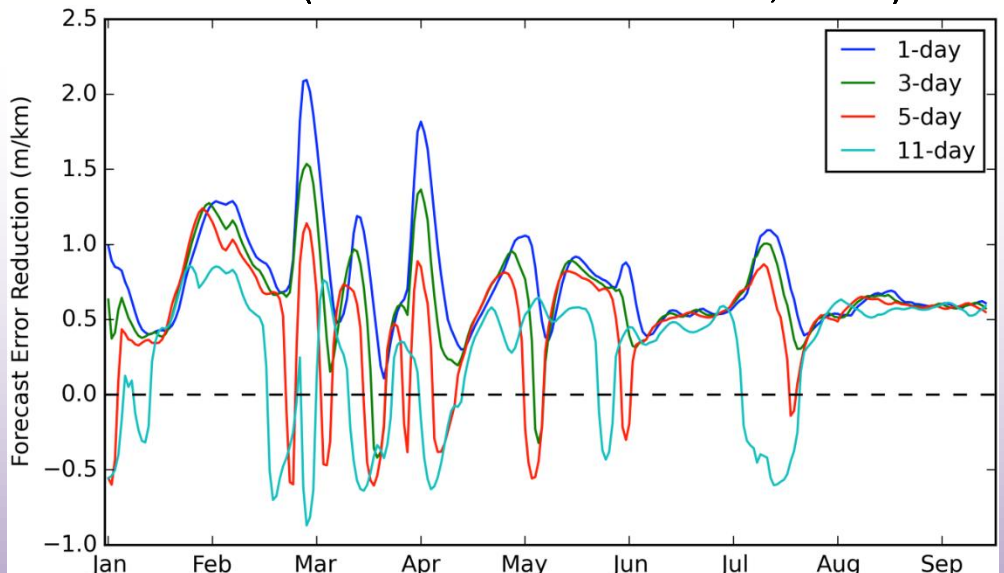
Estimating discharge (Munier et al., 2015)



Estimating bathymetry (Yoon et al., 2012)



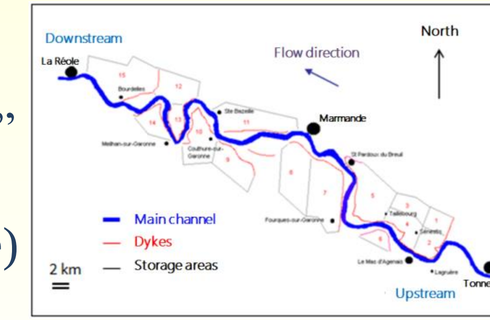
Persistence (Andreadis & Schumann, 2014)



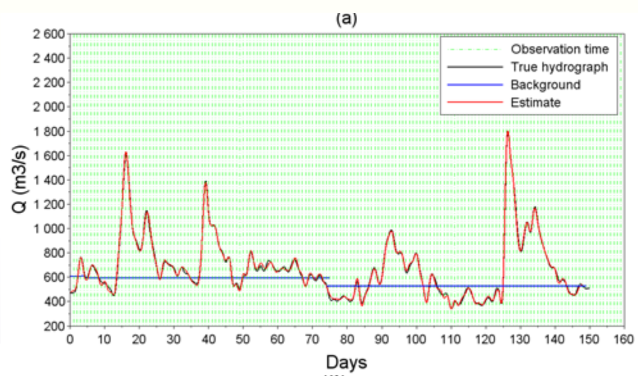
River discharge estimation under uncertainty from in-situ and remote sensing data using variational data assimilation and a full Saint-Venant model

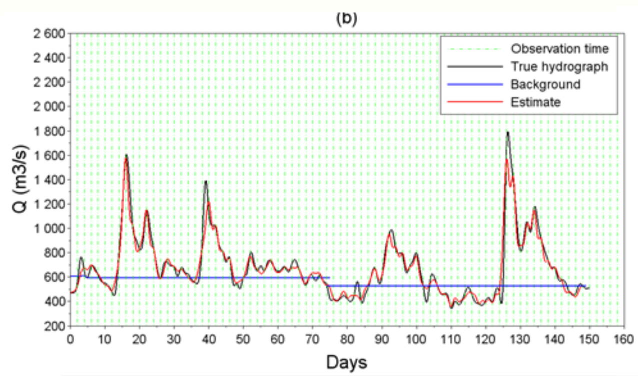
H. Oubanas, I. Gejadze, P-O. Malaterre

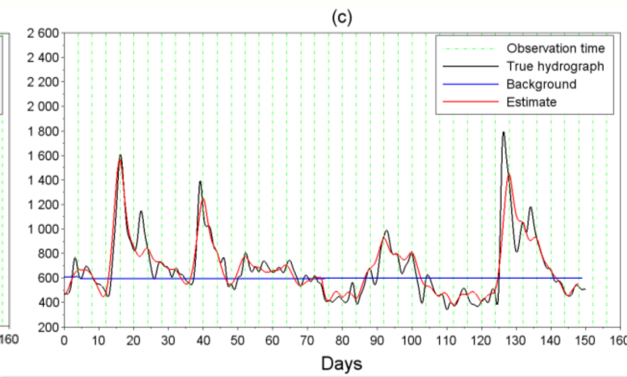
- **1.5D Full Saint-Venant hydraulic model - Irstea/Montpellier:**
  SIC² "Simulation and Integration of Controls for Channels"
- **Variational data assimilation** + Overlapped sliding windows
- **Garonne benchmark -** Downstream reach (Tonneins → La Réole)

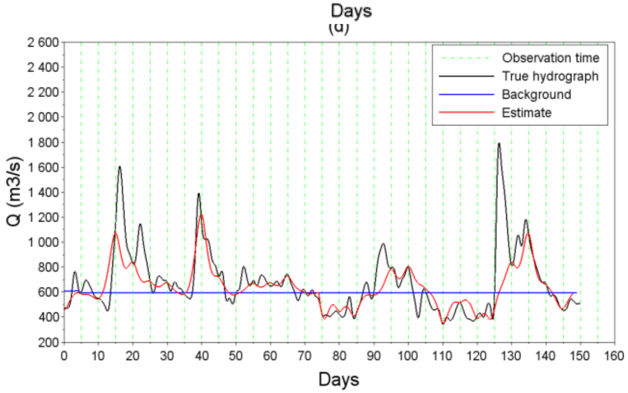


▪ **Estimation of inflow discharge Q assuming exact bed level Z_b and Strickler coefficient K_S.**





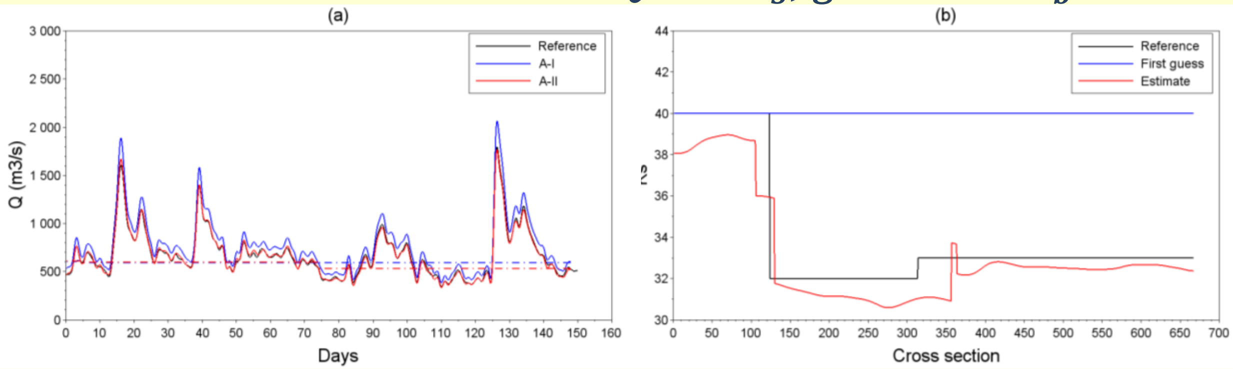




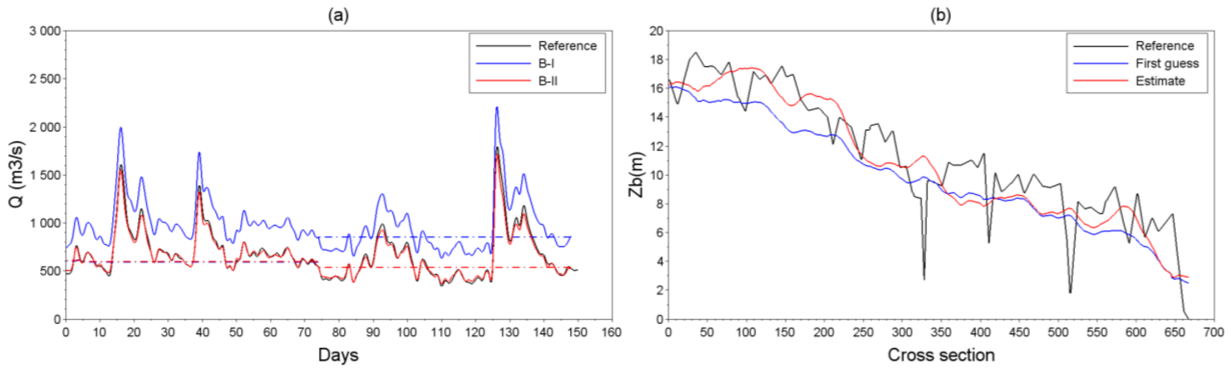
Discharge hydrograph at Tonneins from 01/01/2010 to 31/05/2010 .
(a) 1-day, (b) 2-day, (c) 4-day, (d) 5-day, observation period.

	1-day	2-day	4-day	5-day
Q rRMSE	2.1%	9.5%	12.9%	18.2%

A. Simultaneous estimation of Q and K_S, given exact Z_b



B. Simultaneous estimation of Q and Z_b, given exact K_S



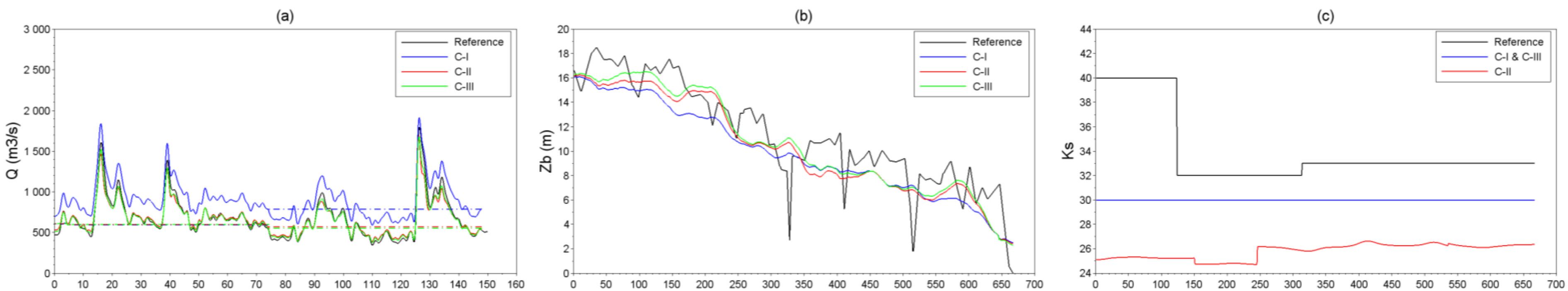
	Q rRMSE	K_S rRMSE	Z_b rRMSE
A-I	12.9%	20.4%	-
A-II	2.6%	3.4%	-
B-I	50.0%	-	5.7%
B-II	3.8%	-	4.9%
C-I	40.5%	13%	5.7%
C-II	7.1%	24.4%	4.7%
C-III	5.1%	13%	4.5%

(I) Estimation of Q solely using the first guess on: **A)** K_S, **B)** Z_b, **C)** K_S & Z_b. (Blue)

(II) Estimation of : **A)** (Q, K_S), **B)** (Q, Z_b), **C)** (Q, K_S, Z_b). (Red)

(III) Estimation of (Q, Z_b) using the first guess on K_S. (Green)

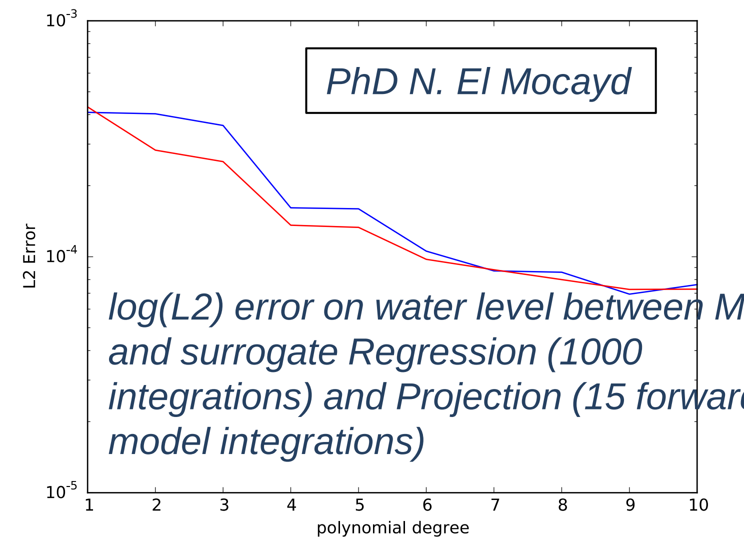
C. Simultaneous estimation of Q, K_S and Z_b ⇒ Equifinality issue!



Note : (a) Solid and dashed lines refers, respectively, to the estimate and the first guess on inflow discharge Q.

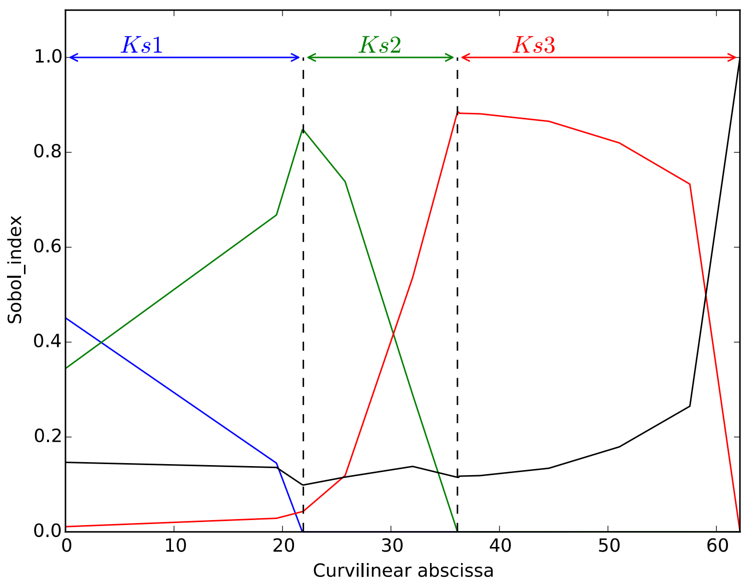
Reduced model for low cost UQ and DA

- Water level is expressed as a truncated sum of polynoms that form an orthogonal basis w.r.t. the uncertain input random variables (Ks,Q)
- Tool for low cost risk assessment and sensitivity analysis
- Identify which variables are predominant for DA
- The PC surrogate model is used in place of the forward model for ensemble-based covariance estimation in EnKF

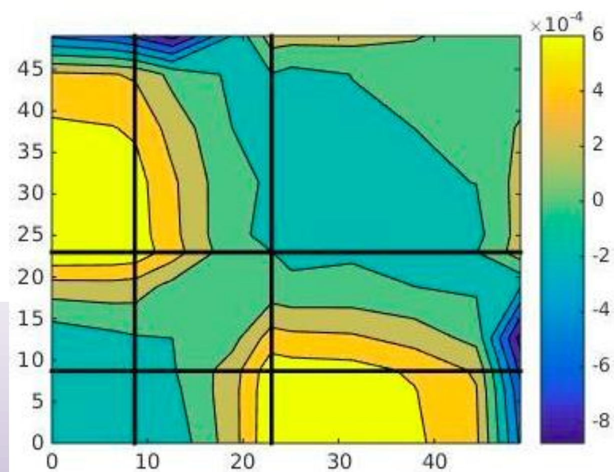


PhD N. El Mocayd

log(L2) error on water level between M and surrogate Regression (1000 integrations) and Projection (15 forwar model integrations)



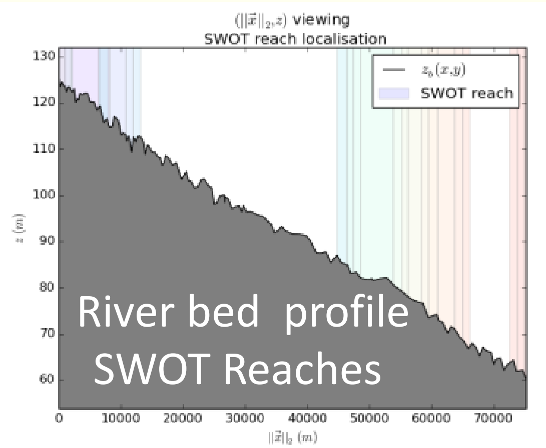
Sobol indices between Tonneins and La Réole w.r.t. Ks and Q

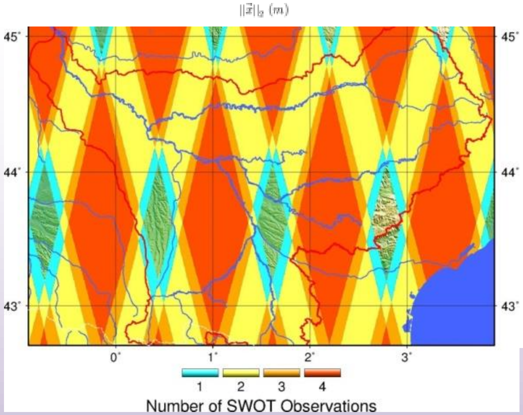


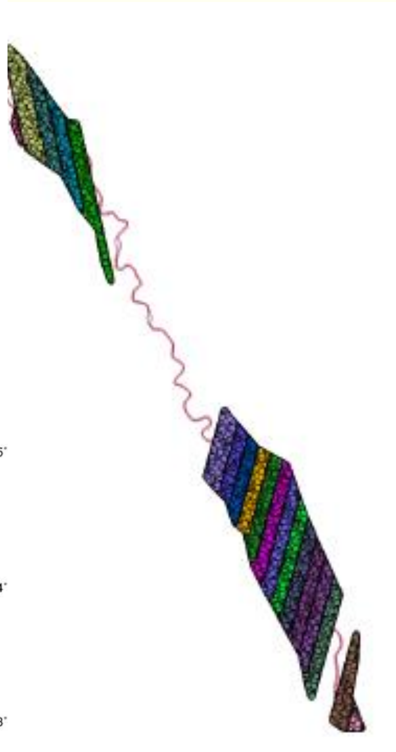
Error on the water level covariance matrix between MC and surrogate estimate

River discharge estimation – DassFlow 0,5D – 1D – 2D Variational DA

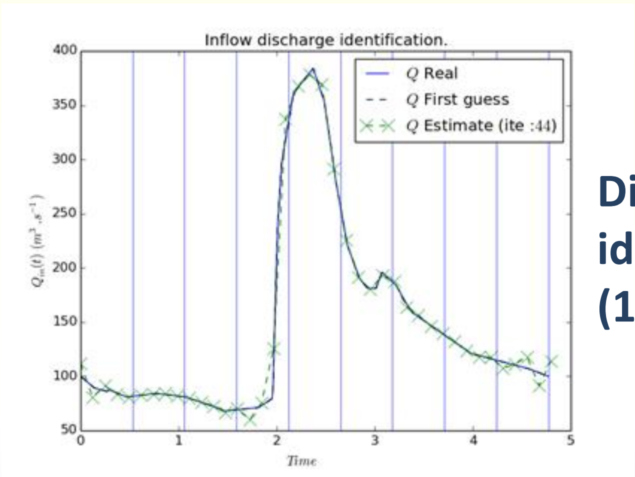
- 0.5D reach averaged - 1D full Saint Venant and 2D Shallow Water
- Variational sensitivities & DA with SWOT like observation operators
- Test cases: Garonne (hierarchical model), Xingu (0.5D-1D) etc



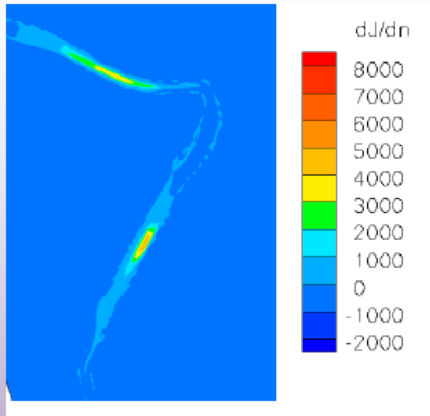




Garonne River, Acsending-descending SWOT tracks

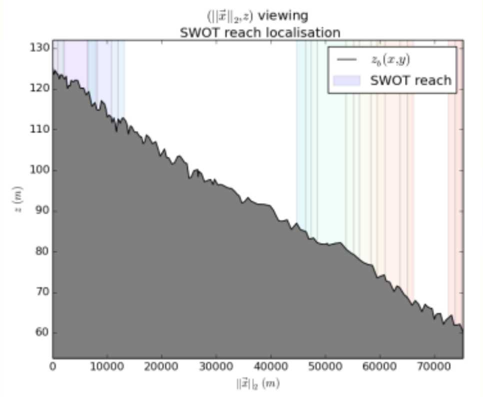


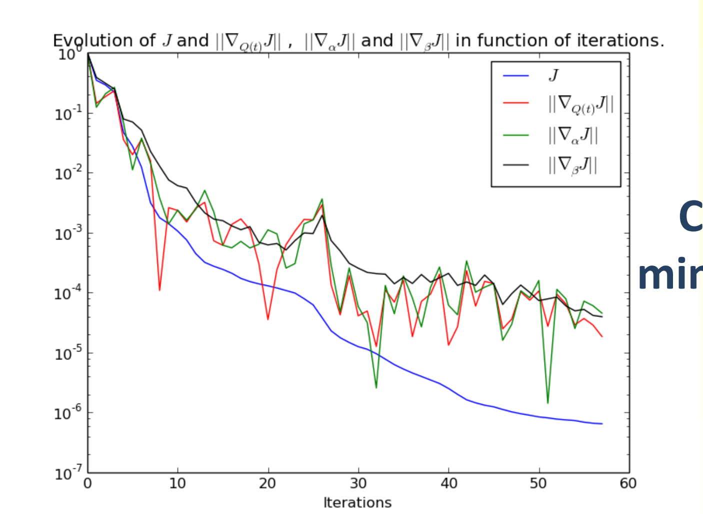
Discharge identification (1D and/or 2D)



Spatially distributed sensitivites (roughness , or bathymetry)

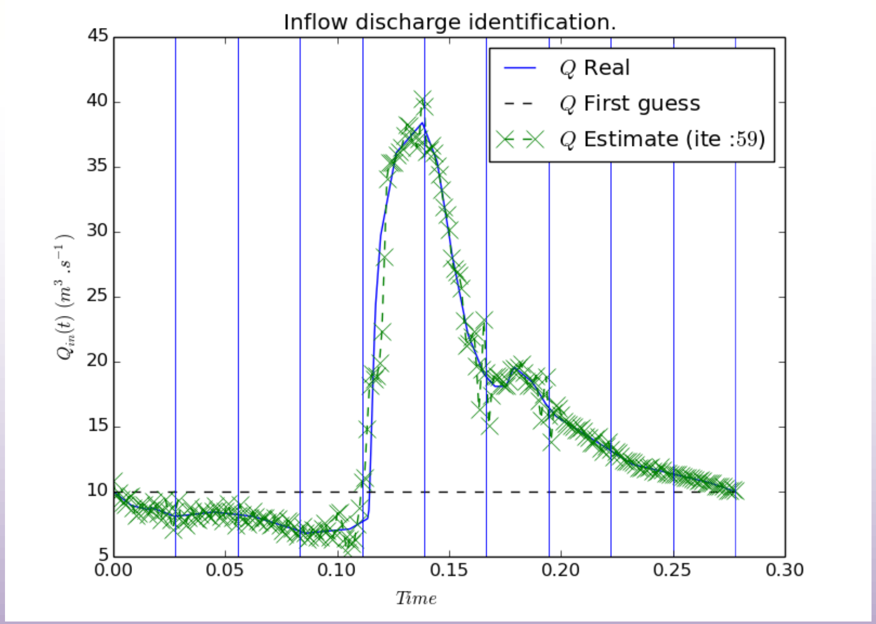
River discharge estimation – DassFlow 0,5D – 1D – 2D Variational DA

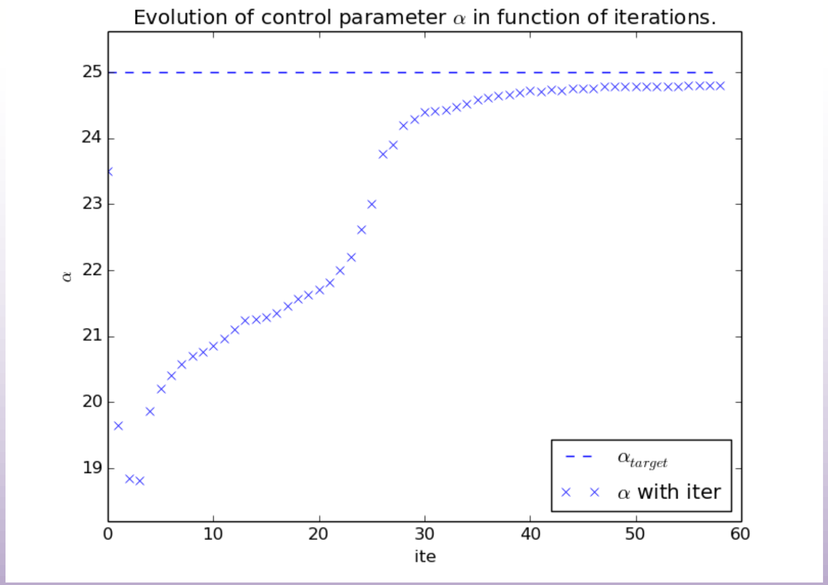




Cost function minimization and gradient

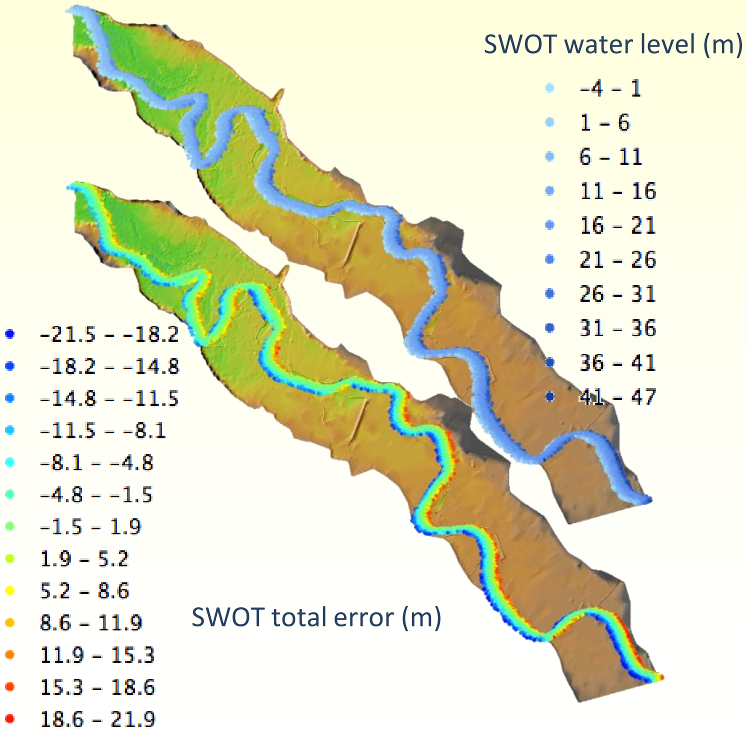
Identification of roughness and discharge

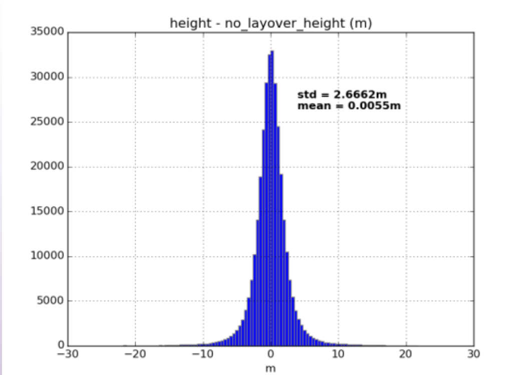




Synthetical SWOT data over the Garonne River (LEGOS et al.)

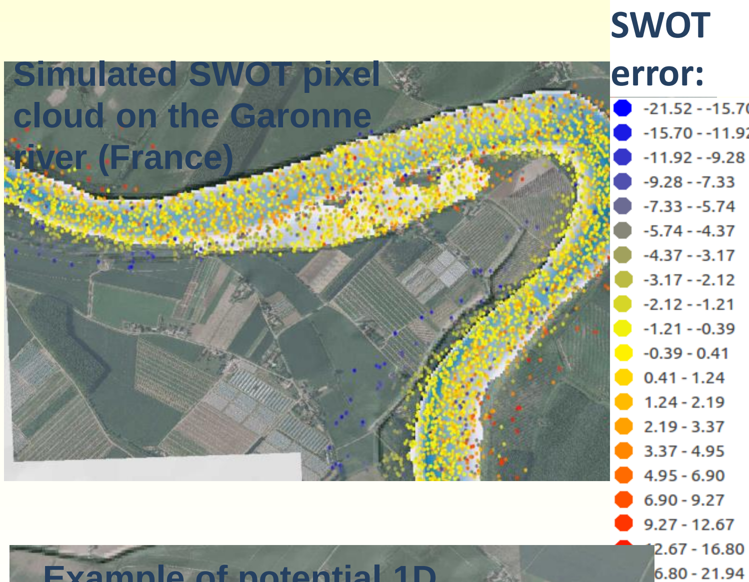
Tools: 1D to 2D unstructured model output mapping → SWOT-HR simulator

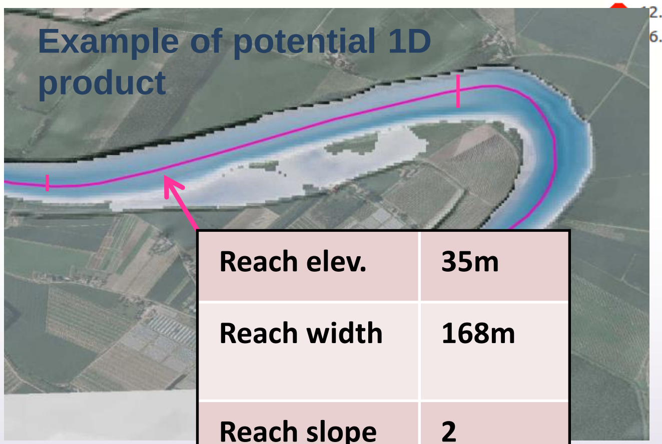




SWOT total error Q = 600 m³/s

LEGOS-CERFACS computation (SWEEP based version)





Reach elev.	35m
Reach width	168m
Reach slope	2 cm/km
Elev. error	…

LEGOS-IMT computation (Python based version)

Conclusions (1/2)

- Possible Identification of couples of river unknowns (Q , Z_b and K_s) given SWOT like observations
- Equifinality problems for the triplet identification (corroborates discharge algorithms conclusions)
- River bed bathymetry data are crucial

Conclusions (2/2)

- Towards a world river bathymetry database?
- Potential fruitful synergies and collaborations (to be defined?), model intercomparisons on Pepsi rivers with:
  - Hydraulic models including DA features.
  - Different hydraulic approaches to define SWOT reaches.
  - SWOT HR simulator data.
  - Fine DA experiments may feedback non DA approaches?

Towards an intercomparison of DA approaches

Potential objectives:

- Extended characterization of discharge inversibility for different hydraulic data/drainage networks configurations.
- Unobserved rivers/lakes: Inversibility at ungauged/unobserved locations?
- Computational: explore different strategies for computational efficiency.
- Impact on forecasting: does assimilation improve model predictability?

Creation of a dedicated ST working group?

database release, blog, teleconfs…